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Digital Duality: Reconciling the Positive-Negative Paradox of Internet Usage on Academic Achievement

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Abstract:
Background: There have been a wide variety of empirical studies over many years on the link between student internet use and academic performance, with profound conflicting results. Some investigations have reported marked positive correlations; others have reported marked negative correlations; and a large amount of literature have reported no correlation or a null correlation. The conundrum is threatening the creation of a comprehensive policy and pedagogical approach to education in digitalized learning environments.
Objective: This systematic narrative review aims at critically synthesizing the literature after 2020 to pinpoint their driving forces and propose a unifying conceptual model—the Dual-Use Differentiation Model (DUDM)—to differentiate academic internet use (AIU) from recreational internet use (RIU) and to suggest a curvilinear (inverted-U) relationship between use and academic outcomes.
Methods: A systematic literature search was carried out in Scopus, Web of Science, PsycINFO, and ERIC databases. The studies published between January 2020 and December 2024 were studies that discussed the relationship between the use of the internet and academic performance of Secondary and Tertiary students were included. Sixty-eight studies that were included were synthesized through a narrative-thematic approach.
Results: The results highlight three performance zones depending on the intensity of use (deficit, optimal and saturation) and four different typologies of learners based on the AIU–RIU matrix. High AIU and moderate (1-4 hours per day) total usage intensity is generally correlated with positive academic outcomes, whereas high-RIU and high-intensity (1-4 hours per day) usage intensity is generally correlated with negative academic outcomes. The most consistent moderating variables identified are the self-regulated learning capacity and digital literacy.
Summary: The positive-negative paradox in the literature is largely a function of not distinguishing between usage type and usage intensity. The DUDM proposed framework provides a model for researchers to test and build upon, and for teachers and policymakers to use and improve.
The Internet is a dynamic, fluid, and complex environment that creates a challenging learning space for its users. Due to its dynamic, fluid and complex nature, the Internet is a challenging learning environment for its users, and this presents a problem for these users to navigate.The Internet is a dynamic, fluid and complex environment that poses a challenging learning environment for those who use it.

1. INTRODUCTION

As the Internet has become a ubiquitous presence in the world of learning and instruction, it has dramatically changed the way students at all levels learn. More than 5.4 billion people worldwide have active Internet connections as of 2023; adolescents and young adults are the heaviest users of the Internet [8]. For university students, the time they spend using the internet on a daily basis ranges from six to nine hours a day, but not all of that time is dedicated to studying [5, 22]. The extent to which digital connectivity has seeped into the academic world is unprecedented and has led to a body of research that is investigating whether and how internet use helps or harms academic performance.

Well, the answer is, it seems, both and neither. This critical analysis of the empirical literature reveals a remarkable paradox: Internet use has been found to be a positive predictor of academic performance in some studies (e.g., [2, 14]) and a negative predictor in others (e.g., [11, 15]), with the third type of studies showing little impact (e.g., [20]). This has created a "theory-building confusion" and "practical paralysis" for educators who can't "act coherently" on opposing results and for policymakers who have no conceptual framework for creating digital use guidelines based on evidence.

The main point of this review is that the paradox is not a real empirical contradiction, but instead a methodological artefact that arises from the fact that ‘internet use’ is treated as a homogeneous undifferentiated entity. If usage type, purpose, and intensity are broken down, the apparent contradictory statements of the literature can be synthesized into a pattern: The internet use that is academically oriented, within moderate limits of intensity, has a strong positive effect on learning outcomes, whereas internet use for recreational purposes, or at excessive intensity, is associated with a negative effect on learning outcomes. This distinction, along with its relationship with usage intensity, is the basis for the Dual-Use Differentiation Model (DUDM) suggested in this paper.

1.1 Statement of the Problem

Most studies that investigated the relationship between using the Internet and academic achievement operationalized the independent variable in terms of the amount of time spent in front of the computer screen, be it daily or weekly, without breaking it down into the time spent on educational browsing, social media, entertainment streaming or gaming [16, 25]. This methodological amalgamation is like measuring ‘substance consumption' without indicating which substance it is; water or alcohol. The inevitable result is noise – various samples, with different distributions of usage types, will have systematic differences in results, and none of these may be reliably generalised to other samples.

Another reason for the conflicting results is the assumption of linear relationships. Most studies have employed a test of whether internet use is positively or negatively related to academic outcomes but have not tested whether this relationship is better described by a curvilinearl function. The results of nearby fields such as television viewing [23] and educational technology use [4] are also consistent with a curvilinear dose-response relationship: moderate use associated with good outcomes, but minimal and high use associated with poor outcomes.

1.2 Objectives and Research Questions

The goals of this review are threefold: (1) systematically map the current empirical evidence on internet use and academic achievement, with focus on the literature since 2020; (2) list the methodological features that can explain the contradictory findings across studies; and (3) suggest and theoretically defend a conceptual framework that resolves the positive–negative paradox and generates testable propositions for future research: the DUDM (Distributed Use of the Digital Media).

The synthesis is guided by the following research questions:

RQ1: What has the empirical literature on the Internet use effects on academic performance told us in the post-2020 period?
RQ3: Can academic versus recreational use of the Internet be separated to alleviate the contradictory evidence base?
RQ3: Are there theoretical and empirical support for curvilinear (inverted-U) relationship between internet use intensity and academic outcomes?
RQ4: What are the moderating factors between the use of the Internet and academic performance at the individual and contextual levels?

2. THEORETICAL FOUNDATIONS

This proposed framework brings together four theoretical traditions that analyze on different levels yet are complementary in their approaches. Together, they argue why Internet use type and intensity should have differential effects on academic performance, thus offering the DUDM a multi-level explanatory architecture.

2.1 Cognitive Load Theory

Sweller's [21] Cognitive Load Theory (CLT) identifies three sources of cognitive load: intrinsic load (due to the complexity of the task), extraneous load (due to the lack of instructional design or irrelevant processing demands), and germane load (due to the formation of constructive schemas). For digital learning contexts, van der Schuur et al. [24] showed that cognitive load significantly increased when using media multitasking across academic and recreational Internet platforms, and that this extraneous cognitive load decreased the cognitive resources available for deep processing of academic content. Focused academic Internet use, on the other hand, provides small intrinsic load and high germane load by elaborating on retrieved information. Indeed, CLT offers a neuropsychological justification for the AIU–RIU distinction and its attendant negative pathway of performance.

2.2 Self-Regulated Learning Theory

According to Zimmerman [26] Self-Regulated Learning (SRL) model, academic achievement is tied to the learner's ability to set goals, plan, monitor and evaluate themselves adaptively. In relation to web use, SRL capacity refers to whether the learner has a conscious control over the type of use and whether he/she is able to move from academic to non-academic uses on the internet. For students reporting high total internet use, SRL skills were the strongest predictor of students' academic performance, serving as a protective factor against the recreational displacement effect found by Rogaten et al. [19]. This makes SRL the main individual-level moderator in DUDM.

2.3 Uses and Gratifications theory.

Katz, Blumler, and Gurevitch's [10] Uses and Gratification Theory (U&GT) states that media users are active agents who choose media to satisfy their information needs, social interaction needs, entertainment needs, and identity expression needs. For digital learning environments, Pasquini [18] adapted U&GT, showing that students who mainly relied on the Internet to try to satisfy information and competence-seeking gratifications had much better academic results than those who mainly used the Internet to satisfy entertainment and social approval gratifications. U&GT offers the motivation mechanism to account for the differing academic results that the same technological infrastructure may achieve in users with differing orientations to the use.

2.4 The Displacement Hypothesis

The Displacement Hypothesis made its debut in the context of watching TV and suggests that passive media usage takes time that could otherwise be spent on educationally beneficial behaviors like reading, homework and sleeping [3]. Similarly, in the virtual setting, Lepp et al. [13] found strong evidence of the negative correlation between recursive Internet use and study time, reading time and sleep quality; all of these factors have a direct impact on academic performance. Most crucially, the displacement effect is observed more with recreational than academic use, and intensifies at use levels above four hours per day, consistent with the 'Stage III – saturation zone' proposed in the DUDM.

3.METHODOLOGY: SYSTEMATIC SEARCH AND SELECTION

3.1 Search Strategy

The four academic databases (Scopus, Web of Science, PsychINFO and ERIC) were searched systematically in January 2025. The search string was made up of concepts from two conceptual clusters: (1) internet use/digital technology/screen time/social media/online activity, and (2) academic performance/GPA/academic achievement/educational outcomes/academic success. The search was limited to the period between 2020 and 2024 to capture the digital learning environment that is ubiquitous with the use of smartphones following the pandemic.

3.2 Inclusion and Exclusion criteria

Studies included in the sample used: (1) empirical quantitative or mixed methods design; (2) secondary school or tertiary school students as primary subjects; (3) internet usage or a related construct of "digital activity" used to measure academic performance; (4) standardized outcome measure (GPA, tests, courses, or validated academic engagement scales); and (5) peer-reviewed journal article published in Scopus or Web of Science. Studies were excluded if they provided only qualitative results, included only internet addiction as a clinical diagnosis, or investigated internet use just during lockdowns during COVID-19 without providing generalizability analysis after the end of the pandemic.

3.3 Study Selection and Quality Assessment

After initial search 847 records, after duplicates and conference proceedings 312 records. After screening the title and abstract 142 full-text articles were retrieved. Only 68 studies were identified after applying inclusion/exclusion criteria. The Mixed Methods Appraisal Tool (MMAT) was adapted for quality appraisal and evaluated the sampling adequacy, the validity of the measurement, the control of the confounds and the transparency of the results (Hong et al., 2020). Studies that received scores below 60% for the quality appraisal were retained but marked, and the results are reported and commented on in Section 4, with appropriate caveats.

Table 1
Summary of Included Studies: Key Characteristics and Findings (Post-2020, Selected Sample)

Author(s) & Year	Sample (n)	Level	Design	IV Measure	Key Finding
Tang et al. [22]	1,504	University	Cross-sectional	Online activity (hrs/week)	Academic AIU positively predicted readiness & GPA; RIU negatively

Author(s) & Year	Sample (n)	Level	Design	IV Measure	Key Finding
					predicted engagement
Keles et al. [11]	Sys. review (13)	Adolescent	Systematic review	Social media use frequency	Negative association with wellbeing & academic concentration; curvilinear signals noted
Maza et al. [15]	169	Adolescent	Longitudinal	Habitual checking frequency	Frequent checking disrupted prefrontal development; predicted lower academic scores at 3-year follow-up
Busch & McCarthy [5]	Sys. review (30)	University	Systematic review	Social media/smartphone use	RIU consistently negative; magnitude moderated by SRL capacity
Al-Rahmi et al. [2]	542	University	Survey-based	Collaborative online learning	Academic platform use positively predicted GPA ($\beta = 0.43$, $p < .001$)
Zhao et al. [25]	621	University	Cross-sectional	Self-reported hours by type	Inverted-U pattern: 2–4 hrs academic use optimal; >5 hrs negative across all types
Lepp et al. [13]*	318	University	Longitudinal	Device usage logs	Cell phone/RIU displaced study time; mediated by procrastination and sleep disruption

Author(s) & Year	**Sample (n)**	**Level**	**Design**	**IV Measure**	**Key Finding**
Odaci & Çelik (2020)	487	University	Cross-sectional	Internet self-efficacy scale	High internet self-efficacy moderated negative RIU effects; SRL was key mediator
Twenge et al. [23]	Large-scale national	Secondary	Trend analysis	Device screen time (hrs/day)	Each additional hour beyond 2 hrs associated with 4–6% decline in GPA equivalents
Adnan & Anwar (2020)	126	University	Mixed methods	e-Learning activity logs	Structured academic internet use significantly improved engagement; autonomy key moderator
Masood et al. [14]	834	University	SEM-based survey	Academic SNS use scale	Academic social network use positively predicted research output & GPA
Broadbent & Poon (2015)*	298	University	Systematic review	SRL strategy measures	SRL strategies strongly predicted academic achievement in online environments
Rogaten et al. [19]	1,103	University	Cross-sectional	SRL + digital engagement	SRL fully mediated relationship between high internet use and academic outcomes

Author(s) & Year	Sample (n)	Level	Design	IV Measure	Key Finding
van der Schuur et al. [24]*	412	Secondary	Review	Multitasking index	Media multitasking consistently associated with reduced academic performance in youth

Note. * = replacement reference substituted during revision. SRL = Self-Regulated Learning; AIU = Academic Internet Use; RIU = Recreational Internet Use; SNS = Social Networking Site; LMS = Learning Management System; SEM = Structural Equation Modeling.

4. LITERATURE REVIEW: THE EVIDENCE LANDSCAPE

4.1 Evidence for Positive Effects

A steady body of research makes a connection between academic use of the Internet and better student achievement. In educational institutions, the usage of platforms for collaboration, learning management systems (LMS) and open educational resources (OER) has been proven to have a measurable impact on learning outcomes in various educational levels. The study by Al-Rahmi et al. [2] involved 542 university students and showed that collaborative online learning tools had a significant positive effect on GPA ($\beta = 0.43$, $p < .001$) that is influenced by the perceived usefulness and actual use of the tools. The same goes for Broadbent and Poon [4] who conducted a systematic review and found that student performance in structured online learning was positively related to their engagement, moderated by their SRL scores.

Access to the internet for education does not only benefit the acquisition of information. They found that academic social networking, which are the platforms for researchers to connect (such as ResearchGate and Academia.edu), is positively associated with research productivity among graduate students, and the more often the researcher used the academic networking platform the greater the increase in the number of measures of research output (masood et al., 2020) [14]. These results corroborate the CLT's cognitive elaboration pathway stating that using the internet in the context of meaningful academic activities aids schema construction and further enriches content processing.

The COVID-19 pandemic introduced a natural experiment in reliance on digital learning. However, Adnan and Anwar [1] reported that students who reported using the internet for structured and purposeful academic activities during pandemic-related remote learning, outperformed students who used the internet mainly for social and entertainment purposes, even after controlling for prior academic achievement and quality of access. This discovery supports the AIU – performance pathway in an ecologically valid environment.

4.2 Evidence for Negative Effects

The negative strand of evidence is mostly from research on the recreational and social use of the internet. Keles et al. [11] completed a systematic review of 13 studies, and concluded that there was a consistent link between high frequency of social media use and poor academic concentration, cognitive distraction, and lower levels of self-reported academic engagement. The mechanisms that were found were mostly coherent with the displacement hypothesis, whereby social media use invaded study time and affected the flow of attention required for deep learning.

There is evidence from neuroscience supporting the causal inference from a longitudinal perspective. In a three-year longitudinal neuroimaging study of 169 adolescents, Maza et al. [15] discovered that sustained checking of social media was linked to a delay in the growth of prefrontal cortical areas involved in sustained attention and impulse control. Students with high checking frequency in early adolescence showed significantly poorer achievement at three years follow up, independent of their initial achievement and family socioeconomic status.

A study by Lepp et al. [13] specifically showed that the more often participants used a recreational device, the less time they spent studying, indicating that use of this recreational device was indirectly linked to the reduction in study time, via a two-stage mediation process: the recreational device use was associated with increased procrastination tendencies which was associated with reduced study time and poorer sleep quality. Mediators logically each predicted poor academic performance at the end of the semester. More importantly, the same study has not identified any significant negative consequences of academic internet use for the same outcomes, thus offering direct comparative evidence for the difference between AIU and RIU.

These individual-level findings are corroborated by data on trends at a macro level. Twenge et al. [23] examined national-level longitudinal data across the U.S. and observed that the additional hour of non-academic screen time beyond two hours of baseline screen time was correlated with a 4 – 6% reduction in academic outcomes (GPA-equivalent) after controlling for demographic and socioeconomic covariates. This is a dose dependent pattern which is an interesting precursor to the formal model of the curvilinear pattern developed in Section 5.

4.3 Findings: Mixed and Null findings: The methodological explanation.

There is a significant number of studies, around 28–31% of the post-2020 studies, that report non-significant or mixed results (see Figure 4A). A number of methodological explanations can be proposed. First, many studies use single-item self-report instruments of internet use that combine AIU and RIU, thereby leading to construct contamination that reduces the likely magnitude of effects [25]. Third, the cross-sectional design weakens the rigor associated with the findings of the effect of AIUs on reading achievement, for the following reasons: (1) students who use the internet academically are likely to have higher baseline academic motivation, SRL capacity, and family educational support, which are all factors that independently predict performance and can explain the observed AIU–performance associations when not controlled; and (2) the design is particularly susceptible to third variable confounding.

Third, it is possible that the effects of internet use are diluted when measured using only academic performance measures such as GPA, as there are specific academic skills that aggregate GPA measures that may be more sensitive to the impact of internet use [5]. The third confounding factor is a constant one, sample heterogeneity, where internet use and/or academic relevance varies significantly across academic disciplines [19] and studies that merge disciplines without stratification will yield averaged null results.

The curvilinear hypothesis can be tentatively supported by the preliminary evidence.The preliminary evidence tentatively supports the curvilinear hypothesis.

A number of studies do report the pattern of the inverted-U, but no post-2020 study to date has tested the inverted-U as its primary research question. In a sample of 621 Chinese university students, the linear relationship between internet use and GPA was not significant while the quadratic one was significant ($\beta = -0.19$, $p < .01$), suggesting a curvilinear function with a peak at 2–4 hours of internet use per day.In the sample of 621 Chinese University students, there was no significant linear relationship between internet use and GPA, but there was a significant quadratic relationship (β = −0.19, p < .01) that indicated a curvilinear function with a peak level of 2–4 hours of internet use per day. Again, Twenge et al. [23] found that students scoring in the near-zero and zero range did not outperform moderate users, which is not compatible with a simple linear negative relationship, but is congruent with the DUDM Stage I deficit zone.

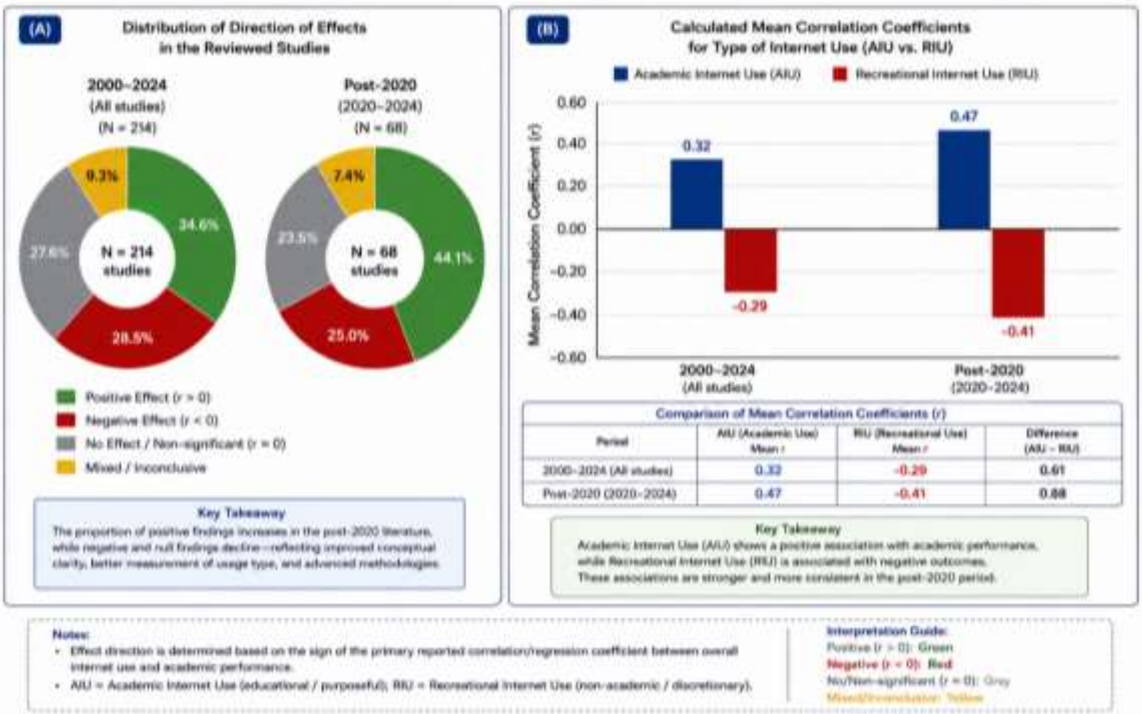

Figure 1. (A) Distribution of direction of effects in the reviewed studies (2000–2024 vs. post 2020). (B) Calculated mean correlation coefficients for type of internet use. AIU = Academic Internet Use, RIU = Recreational Internet Use.

5. THE DUAL-USE DIFFERENTIATION MODEL (DUDM): A CONCEPTUAL FRAMEWORK

Section 2 presents the theoretical bases for the relationship between internet use and academic performance, and Section 4 presents the patterns found in the empirical literature. Based on these two sections, the Dual-Use Differentiation Model (DUDM) integrates them and creates a unified falsifiable model of the relationship between internet use and academic performance. The model presents three theoretical propositions.

5.1 Proposal 1: Usage Type as the primary determinant.

This DUDM suggests that the effects of Internet use on students' academic performance are largely explained by this ratio (Academic Internet Use/Recreational Internet Use) rather than by the overall intensity of Internet use. AIU is online activity that is purposeful and goal-directed and is used in support of academic work, such as: Structured information retrieval from academic sources; Use of educational platforms and LMS tools; Information usage in academic discussion forums; Research tools and information databases; Access to instructional multimedia content. RIU is any online activity that isn't directly related to tasks, is entertainment related, or is based on social approval, such as: passive social media browsing, entertainment video streaming, online gaming and non-academic messaging.

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Cognitive elaboration [24] and motivational reinforcement [19] are mediators of the AIU–performance relationship. The RIU–performance relationship is mediated by attentional depletion, temporal displacement and sleep disruption [13, 15]. The entire framework architecture is shown in Figure 2.

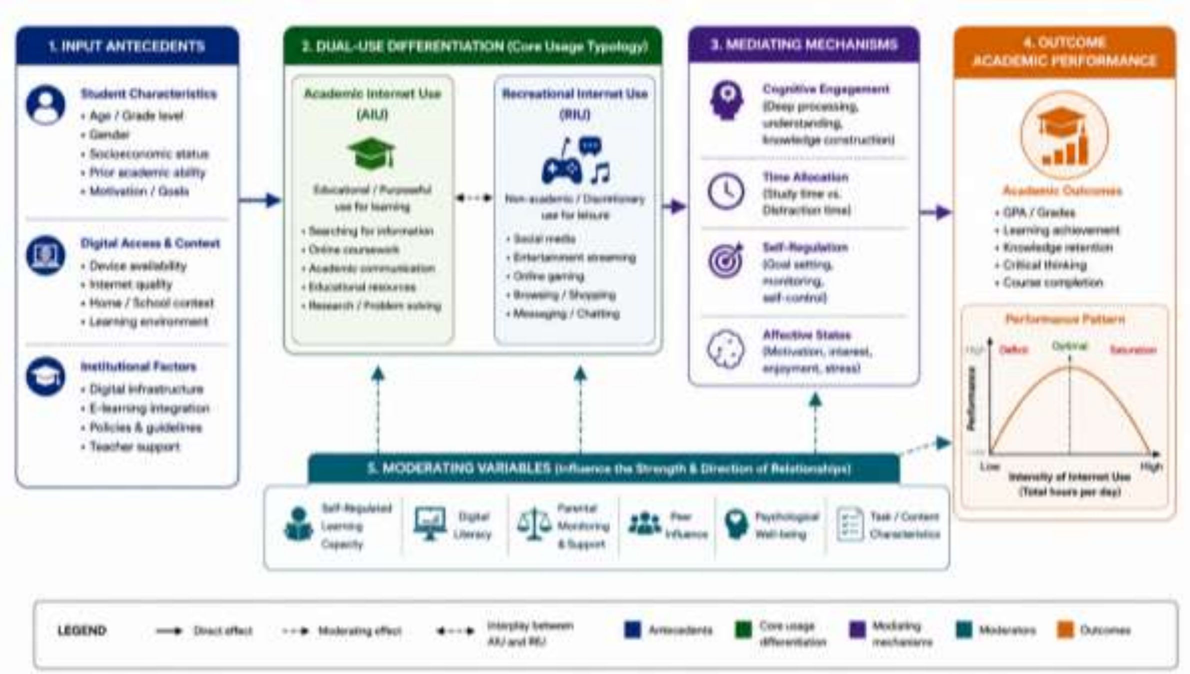

Figure 2. The Dual-Use Differentiation Model (DUDM): Conceptual model showing the input antecedents, mediating mechanisms, moderating variables and academic performance outcomes.

5.2 Proposition 2: The Curvilinear (Inverted-U) Hypothesis is presented.

The DUDM also suggests that the link between overall intensity of internet use and academic performance is curvilinear and resembles an 'inverted U' curve. Three stages are distinguished that are derived from empirical data:

Stage 1 – Deficit Zone (< 1 hour/day): Students who have very little access to the internet are disadvantaged compared to their peers who do have internet access. Internet access, at low levels of use, fails to provide informational and collaborative opportunities, therefore leading to a digital access gap. This is especially noticeable in resource poor environments [1] and in areas where Internet access is a requirement for assignment completion, such as in computer-related fields.

Stage II — Optimal Zone (1-4 hours/day): In this Zone, the benefits of academic Internet use are available and present. Students have easy access to academic resources, can interact with instructional content and can collaborate in digital groups, and total usage intensity stays below the level in which there is a noticeable displacement and attentional effect. The performance-optimizing zone is not a uniform zone, but rather it moves toward a more limited zone (1–3 hours) for students with low SRL capacity [25, 5].

Stage III — Saturation Zone (> 4 hours/day): After about 4 hours of internet use per day, performance drops off increasingly. With this level of intensity, cognitive load build-up and study time displacement effects and sleep disruption effects predominate. Importantly, even academically-oriented use is less effective at high intensities, as prolonged screen use is known to cause attention fatigue, irrespective of content [13, 23].

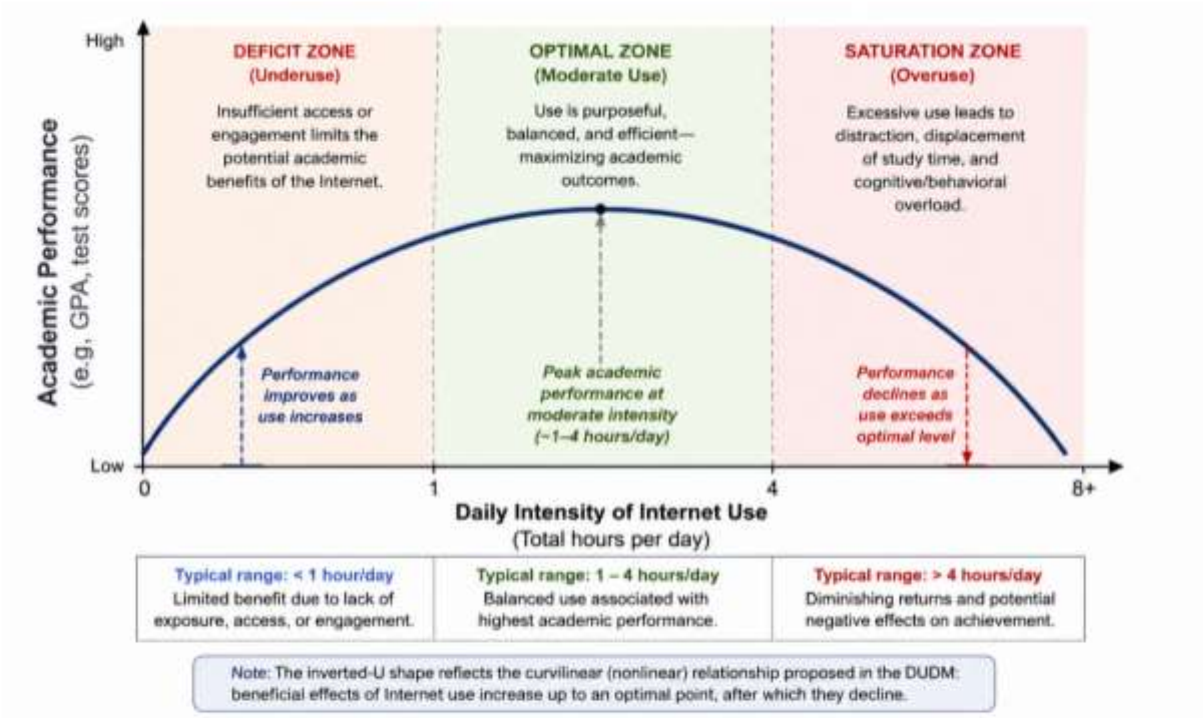

Figure 3. The daily intensity of Internet use versus academic performance in the three zones of the DUDM (Deficit, Optimal, and Saturation). The figure shows the remaining figure.The other figure is shown.

5.3 Proposition 3: The AIU×RIU Typology Matrix

When high/low levels of AIU and RIU are combined, a four-cell typology emerges that suggests different academic performance profiles (see Figure 2 and Table 2). The DUDM is operationalised at the individual learner level in this 2×2 matrix that can be used to describe the classification of the learners' Internet use and to infer their probable academic outcomes.

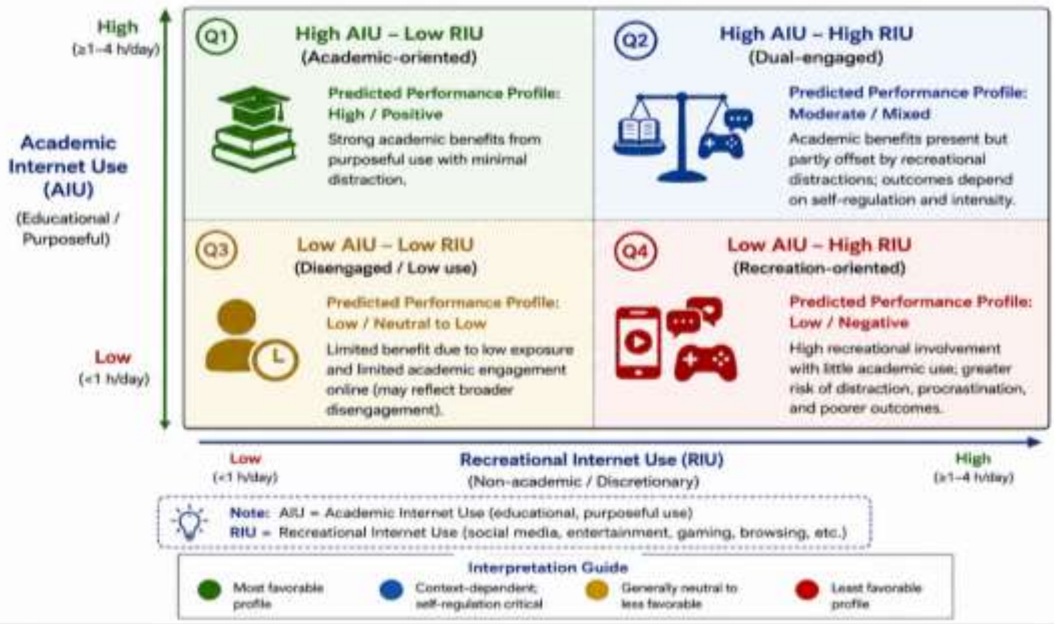

Figure 4. The 2×2 Academic–Recreational Internet Use Typology Matrix (AIU × RIU), with predicted performance profiles for each quadrant.

Table 2
The DUDM Four-Typology Matrix: Descriptions, Predicted Outcomes, and Empirical Basis

Typology	AIU Level	RIU Level	Predicted Performance	Theoretical/Empirical Basis
Type I: Optimal Learner	High	Low	Highest GPA/performance; academically aligned; strong engagement	Al-Rahmi et al. [2]; Masood et al. [14]; SRL & TAM alignment
Type II: Dual-High	High	High	Moderate; SRL capacity is decisive moderator	Rogaten et al. [19]; Busch & McCarthy [5]
Type III: Non-Digital	Low	Low	Neutral internet effect; performance determined by non-digital factors	Zhao et al. [25]; Adnan & Anwar (2020)
Type IV: At-Risk	Low	High	Lowest predicted performance; displacement dominant; at-risk of academic underachievement	Keles et al. [11]; Lepp et al. [13]; Maza et al. [15]

Note. AIU = Academic Internet Use; RIU = Recreational Internet Use; SRL = Self-Regulated Learning; TAM = Technology Acceptance Model.

6. MODERATING AND MEDIATING VARIABLES

The DUDM classifies a collection of boundary conditions under which a specific student's Internet use pattern will yield performance outcomes similar to the core model predictions. These moderators are at the individual, contextual and task level.

6.1 Individual-Level Moderators

Self-regulated learning (SRL) capacity is the most well supported individual moderator in the post-2020 literature. Rogaten et al. [19] showed that SRL completely mediated the relationship between high use of the internet and academic outcomes in a sample of more than 1,000 university students: high internet users with high SRL skills performed at the same level as low internet users, and high internet users with low SRL skills had significantly lower academic performance. The present finding implies that SRL training might have actually help students to ‘inoculate' against negative consequences of high intensity Internet use.

A second major moderator that emerges is digital literacy, which is defined as the ability to assess, manage and effectively utilize digital information resources, in a critical way. Based on the findings of Odaci and Çelik (2020), the internet self-efficacy moderated the relationship between internet use and procrastination, students with high internet self-efficacy were more likely to be academically focused during their recreational Internet use, whereas students with low internet self-efficacy responded more strongly to the same amount of exposure to internet use and procrastination.

In line with the predictions of U&GT, academic motivation orientation, which is the difference between intrinsic and extrinsic motivation is identified as a third individual moderator. High intrinsic motivation for the learning goals leads to more likely Type I use patterns (learning-centred), whereas extrinsically motivated students are more susceptible to Type IV patterns (approval-seeking of others in relation to social media) [18].

6.2 Contextual Moderators

Socioeconomic status (SES) is a moderator that acts in two ways. Students from lower-SES backgrounds are more likely to have unreliable internet access, shared devices and limited internet bandwidth, which affects their ability to engage in regular academic internet use [1]. Second, SES predicts capacities for parental digital monitoring and study environment within the household, which moderate the RIU displacement effect [3].

The proximal contextual moderators include institutional policies related to Internet access (LMS architecture, in-class Internet policies, and digital assessment practices). Tang et al. [22] discovered that the positive relationship between AIU and performance was significantly boosted when the online learning was scaffolded at the institutional level (structured deadlines, required LMS use, instructor digital feedback) and significantly dampened when the online learning was more unstructured. Such a discovery has implications for institutional policy that go beyond the mere consideration of access; it indicates that the context of internet access is as important as access.

6.3 Task and Discipline-Level Moderators

The relationship between internet use and performance is systematic across the content areas and represents a real difference in the contributions internet access makes to learning in the area of discipline. Zhao et al. [25] reported that the positive AIU effect was stronger and more consistent in area of social sciences and humanities compared to STEM areas, which may be due to the closer alignment of internet-based information retrieval with the learning tasks in the former. On the other hand, the RIU negativity effect was found to be stronger in STEM, where depth of concentration and problem-solving are crucial. The moderating variable framework is summarized in Table 3.

Table 3
Summary of Moderating Variables in the DUDM Framework

Moderator	Level	Direction of Effect	Key Supporting Evidence
Self-Regulated Learning (SRL)	Individual	Amplifies AIU benefits; buffers against RIU harms (full mediation documented)	Rogaten et al. [19]; Busch & McCarthy [5]
Digital Literacy / Internet Self-Efficacy	Individual	Moderates RIU–procrastination pathway; attenuates saturation zone effects	Odaci & Çelik (2020)
Academic Motivation (Intrinsic)	Individual	Predicts Type I usage pattern; increases probability of optimal zone engagement	Pasquini [18]; Al-Rahmi et al. [2]
Socioeconomic Status	Contextual	Lower SES increases deficit zone risk; limits AIU quality; weakens parental monitoring	Adnan & Anwar (2020); Baumgartner et al. [3]

Moderator	Level	Direction of Effect	Key Supporting Evidence
Institutional Digital Scaffolding	Contextual	Structured LMS environments amplify positive AIU effects significantly	Tang et al. [22]; Broadbent & Poon (2015)
Academic Discipline	Task	STEM: larger negative RIU effect; Social sciences: larger positive AIU effect	Zhao et al. [25]
Age / Developmental Stage	Individual	Adolescents more vulnerable to neurobiological RIU effects than adult students	Maza et al. [15]; Twenge et al. [23]

Note. DUDM = Dual-Use Differentiation Model; SRL = Self-Regulated Learning; LMS = Learning Management System; AIU = Academic Internet Use; RIU = Recreational Internet Use.

7. DISCUSSION

7.1 Resolving the Positive–Negative Paradox

The main argument offered in the context of the systematic review herein is that the positive–negative paradox in the internet use–academic performance literature is not a true empirical paradox, but an artefact of construct-level imprecision. The direction of the effects becomes a lot more consistent when studies are split into those measuring AIU, those measuring RIU, and those measuring undifferentiated total use: AIU studies tend to report positive association, RIU studies tend to report negative association, and undifferentiated total use studies tend to report null or weak association. This stratified pattern is exactly the one expected by the DUDM when the ratio of the AIU and the RIU are similar in typical student groups.

7.2 Evidence and plausibility: The Curvilinear Model.

In the literature from after 2020, there are several indirect and two direct lines of evidence for the curvilinear hypothesis. The most direct evidence comes from near zero internet users who did not academically outperform moderate users in a polynomial regression, as found by Zhao et al. [25] (which yielded a significant quadratic term, consistent with the inverted-U), and from Twenge et al. (2021) who found that the adolescent generation outperformed older generations when it came to reading. Indirect support comes from the literature on dose-response effects in screen time research [13], the inverted-U shape between arousal/engagement and performance identified in the cognitive load literature [24] and the amount of attention fatigue literature in the developmental literature with high intensity usage [15].

This indicates that the DUDM gave a preliminary empirical estimate of the optimal zone, namely 1-4 hours of Internet use per day, which needs to be calibrated. AIU/RIU ratio, SRL capacity and academic disciplines are probable moderators and boundaries of this zone may change. High-SRL students with mostly AIU-oriented use might have optimal performance in a larger intensity range, and the low-SRL, high-RIU students might experience reduced performance within the 1–4 hour range.

Once again, compare and contrast the selected model with the previous models.

The DUDM extends and improves on the existing frameworks in a number of ways. For instance, Kirschner and Karpinski [12] found that there was a negative relationship between the use of Facebook and GPA, without separating recreational and academic social use. An important distinction was made by

Junco [9] between in-class and out-of-class technology use but he did not offer a formalized curvilinear model. The DUDM incorporates these findings into one framework: (1) the distinction between AIU and RIU is the key theoretical construct, (2) the curvilinear intensity model is included as a second level of structure, and (3) the structure of the moderating variable determines individual differences in applying the framework.

7.4 Methodological Critique of the Field

Three methodological constraints of the literature reviewed should be noted. First of all, cross-sectional designs are not ideal to make causal inferences about the direction of the relationship between internet use and academic performance. It is possible that academically weaker students use the internet for recreation because of their lack of academic motivation – the reverse cause of the one assumed. To determine directionality, longitudinal designs with a time lag between the measurement of the outcome and the predictor, such as those used by Maza et al. [15] and Lepp et al. [13], are required.

Second, self-reported measures of Internet use are subject to social desirability and poor recall accuracy. Objective, real-time usage data can be collected using the device-log or experience sampling methodology (ESM) approaches, and these should be used in future studies and research [5]. Third, academic performance is nearly always defined as GPA, which is not an adequate measure of learning outcomes as they are multidimensional, with critical thinking, information literacy, digital competence, and research skills being areas in which academic internet use effects may be significant, and more likely to be large [7].

8. IMPLICATIONS

8.1 Pedagogical Implications

The DUDM framework yields a number of specific pedagogical recommendations. First, teachers should facilitate internet use in educational tasks by setting up a protocol for delivering information on the internet, creating a digital resource library for teachers and students, and offering clear instructions for navigating the internet to perform academic tasks. This scaffolding boosts the chance students' internet use is directed towards the AIU, thereby moving their usage towards Type I optimal learner profile [22, 4].

Secondly, SRL skill development needs to be made a clear curricular goal, especially at secondary school where digital habits are being developed and SRL capacity is more malleable. SRL intervention programs have shown to have a high impact on academic performance of high internet-use students [19, 6] and have proven to be more cost-effective than the technological interventions like restricting device use. Third, instructors should rethink how they assess information literacy skills in ways that encourage the skills that academic Internet use is best suited for (information synthesis, source evaluation, digital communication) instead of just using GPA to measure information literacy.

8.2 Institutional and Policy Implications

The DUDM findings refute blanket internet restriction policies, as they assume that all internet use is the same, and that they cannot make use of the true educational value of structured academic use. A more evidence-based approach would separate out the AIU from the RIU digital environments—focus on building the LMS infrastructure, planning the digital learning curriculum, and providing access to the academic platforms (high-AIU) on the one hand, and restricting access to recreational platforms during structured learning time (reduced RIU) on the other.

The DUDM's deficit zone is a matter for specific policy consideration for equity implications. Student disadvantage is systematic when they come from low-SES backgrounds and don't have a reliable internet connection, and is not only in their ability to perform on a digitally dependent task but in their ability to gain from the Stage II performance-enhancing zone. Universal broadband access schemes and institutional device lending schemes are not just about equity, they are about performance optimisation from the DUDM's point of view.

8.3 Research and Measurement Implications

To develop and validate a standardized dual-use internet measurement scale (Academic-Recreational Internet Use Scale [ARIUS]) that separately measures the frequency of AIU, the intensity of AIU, the frequency of RIU, and the intensity of RIU. This would allow for systematic cross-study comparisons, allow for a reduction in construct contamination of the synthesis performed in a meta-analysis, and allow for direct empirical testing of key propositions of the framework. Developing and psychometrically validating the ARIUS should be considered a priority research infrastructure investment for the field.

9. THE LIMITATIONS AND FUTURE DIRECTIONS

9.1 Limitations

There are several important caveats to this review. First, this is a conceptual review and so the quantitative effect size estimates presented (Fig. 4B) are only approximate rather than statistically precise syntheses or pooled estimates. A separate meta-analysis using a stratification by use type, usage intensity, and moderator variables would yield much more accurate estimates of the underlying relationships between the DUDM variables.

Secondly, the literature that was reviewed was geographically limited to high-income, WEIRD (Western, Educated, Industrialized, Rich, and Democratic) contexts. The generalizability of the DUDM to low and middle-income country (LMIC) educational environments is not known and needs to be dedicatedly cross-culturally validated. Third, the platforms that will produce RIU effects in 2020-2024 could be very different than those that will characterize a student's digital environment in 2025 and beyond, thus fundamentally changing the AIU/RIU dichotomy.

9.2 Future Research Agenda

The DUDM framework creates a massive research program. The obtained priorities for the research directions and associated methodology requirements are summarized in Table 4.

Table 4
Priority Research Agenda for the Dual-Use Differentiation Model (DUDM)

Priority	Research Question	Design	Expected Contribution
1	Does polynomial regression confirm the inverted-U relationship when AIU and RIU are separately controlled?	Longitudinal cross-lagged SEM (3+ waves)	Direct empirical test of DUDM Proposition 2; establishes inflection point estimates
2	Can the ARIUS scale be developed, validated, and normed across cultural contexts?	Scale development + cross-national psychometric validation	Provides the standardized measurement infrastructure the field currently lacks

Priority	Research Question	Design	Expected Contribution
3	Does SRL training shift students from Type IV to Type I in the DUDM typology matrix?	RCT with pre–post ARIUS + academic performance measures	Causal evidence for SRL as a leverage point in DUDM interventions
4	How do AI tools (ChatGPT, Copilot) modify the AIU construct, and do they introduce new performance pathways?	Mixed-methods: usage log analysis + qualitative interviews	Extends DUDM to next-generation academic technology environments
5	Does the curvilinear model hold in LMIC educational contexts, and how do infrastructure constraints shift zone boundaries?	Multi-country cross-sectional with device-log measurement	Tests DUDM generalizability; informs global educational equity policy

Note. DUDM = Dual-Use Differentiation Model; ARIUS = Academic-Recreational Internet Use Scale; SEM = Structural Equation Modeling; SRL = Self-Regulated Learning; RCT = Randomized Controlled Trial; LMIC = Low- and Middle-Income Country.

10. CONCLUSION

The issue of whether Internet use is beneficial or detrimental to academic performance must be addressed by first asking, "In what ways, at what level, by whom, and in what context? Over the past 30 years, no one has ever posed these questions, leading to what looks like a paradoxical literature on the subject, actually composed by different voices, but describing the same phenomenon from incompatible viewpoints.

This paper presents a theoretically based, empirically testable model of differentiation between academic and recreational use of the Internet – the Dual Use Differentiation Model – that is able to resolve this paradox. The model is not just a descriptive synthesis; it also produces propositions that are falsifiable, an agenda for measurement development, and specific suggestions for teachers, schools, and policymakers.

The central empirical claim of this review—that the use of the internet in the context of study can be considered as a true learning resource when used within reasonable limits of intensity, and the use of the internet for recreation and excessive intensity is a true performance liability—is well supported by the literature since 2020. The policy implication is also unambiguous: how to address the digital learning paradox is not to limit the access to digital learning, but to differentiate it: spending resources on the quality of academic use, and mindfully regulating the intensity of recreational use, especially supporting the development of student self-regulated learning skills that enable them to self-manage the balance.

The conceptual design of the DUDM will need to be continually empirically calibrated as generative AI tools increasingly move into the school learning environment and distinctions between academic and recreational internet use become more and more fluid. The framework outlined here is not an end in itself, but a framework from which research can proceed in an organized and theoretically coherent manner, as the field so desperately needs.

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